

EXHIBIT 161

PUBLIC

HIGHLY CONFIDENTIAL – SUBJECT TO PROTECTIVE ORDER

**UNITED STATES DISTRICT COURT
FOR THE EASTERN DISTRICT OF VIRGINIA**

UNITED STATES OF AMERICA,
et al.,

Plaintiffs,

v.

GOOGLE LLC,

Defendant.

Case No. 1:23-cv-00108-LMB-JFA

**Expert Report of Judith A. Chevalier
January 23, 2024**

HIGHLY CONFIDENTIAL – SUBJECT TO PROTECTIVE ORDER

148. Altogether, the data above contradict Prof. Simcoe’s basis for his analysis, which assumes that the FAAs are collectively and individually similar to a “representative advertiser.”³⁴⁶ Therefore, Prof. Simcoe’s apportionment analysis is unreliable for the purposes of estimating the share of any AdX overcharge borne by each FAA.

b) Advertisers Differ in their Price Sensitivity

149. As described above, inherent in Prof. Simcoe’s apportionment analysis are assumptions that (i) each of the FAAs faces identical demand and supply curves for the types of impressions that it purchased as every other FAA, (ii) the FAAs face the same demand and supply curves for the types of impressions purchased on their behalf as the average advertiser, and (iii) the FAAs’ ad agencies are just as responsive to revenue share changes as the average advertiser or ad agency purchasing open web display inventory via AdX.³⁴⁷

150. To test these assumptions, I apply Prof. Simcoe’s method of estimating demand elasticities, using the 2023 Log-Level GAM Data, with one modification.³⁴⁸ Prof. Simcoe’s

³⁴⁶ Simcoe Report, ¶ 127.

³⁴⁷ Simcoe Report, Sections IV.B.2, V.B.1, and V.B.2.

³⁴⁸ The data that I use to perform my analysis mirrors Prof. Simcoe’s filtering choices, except that I base my analysis on a 1 in 100 random sample of the 2023 GAM log-level data, rather than the 1 in 100,000 sample that Prof. Simcoe uses. Simcoe Report, ¶ 281. As such, the sample that I use, which constitutes approximately 1.1 million AdX advertisers and 254 million AdX impressions, is approximately 1,000 times larger than the sample that Prof. Simcoe uses. See Exhibit 35. Exhibit 35 shows that if I perform Prof. Simcoe’s analysis on my sample, the implied aggregate elasticity and incidence estimates are similar to the results that Prof. Simcoe reports using his sample. My larger sample allows me to examine a larger number of auctions per advertiser, on average, which should lead to more reliable advertiser-level elasticity estimates than advertiser-level elasticity estimates that are based on a smaller number of auctions per advertiser. For the same reason, I focus on advertiser-level results for advertisers that won at least 25 AdX queries. For the purposes of my analysis, I use the field anonymised_advertiser_id to identify advertisers in the 2023 GAM data. I understand that this field reflects the landing page of the winning ad and thus an individual FAA may be associated with multiple “advertisers” in the 2023 GAM data. See Email from Laura Onken, “2021.08.12 Google Ad Manager Data Schema Proposal.pdf,” August 12, 2021, at PDF p. 3. To perform my analysis, I follow the same methodology to estimate advertiser demand elasticities as Prof. Simcoe. See Simcoe Report, ¶ 205. I focus on Prof. Simcoe’s method that estimates advertiser demand elasticities by examining the effect of hypothetically raising both the HOB and floor prices, which is the method of estimating elasticities that Prof. Simcoe uses to estimate advertiser incidence; however, I also report demand elasticity estimates based on the other simulation method Prof. Simcoe reports demand elasticities for, which involves only examining the effect of hypothetically raising the HOB. See Simcoe Report, ¶¶ 205, 242. Similarly, I focus on two of the five price increases Prof. Simcoe analyzes: (i) a 6.18 percent price increase (his preferred price perturbation to estimate elasticities), and (ii) a 2.5 percent price increase; however, I also include results associated with the other price increases Prof. Simcoe analyzes. See Simcoe Report, Figure 21.

HIGHLY CONFIDENTIAL – SUBJECT TO PROTECTIVE ORDER

method aggregates all queries won by AdX bidders and then examines the effect of hypothetically raising the prices (by 2.5 to 10.0 percent) on that aggregated data. Such aggregation abstracts away from the fact that different advertisers compete for a systematically different set of impressions. For example, Prof. Simcoe speculates that the Army might use its advertisements to meet recruiting targets.³⁴⁹ If so, the Army is likely systematically involved in different auctions for different impressions than, say, the American Association for Retired Persons, or, even other FAAs (*e.g.*, the USPS). I modify Prof. Simcoe’s method to examine the effect of such price increases on a more disaggregated basis to better reflect the auctions that each advertiser participates in. Specifically, I partition the data into distinct subsamples consisting of queries won by each AdX bidder.³⁵⁰ I then apply Prof. Simcoe’s method to estimate the elasticity specific to each of these samples. This disaggregation allows me to calculate a demand elasticity for the set of impressions won by a specific AdX bidder (*i.e.*, the marketplace is segmented by the identity of the winning bidder). I refer to these elasticities as “disaggregated advertiser demand elasticities.”³⁵¹

151. My analysis reveals that these disaggregated advertiser demand elasticities are very different from each other, ranging from 0.00 to -16.18 using Prof. Simcoe’s preferred “price perturbation” to estimate these elasticities (6.18 percent),³⁵² and ranging from 0.00 to -40.00 using Prof. Simcoe’s alternative price increase of 2.50 percent.³⁵³ Thus, the disaggregated advertiser demand elasticities span a much wider range than the -1.57 to -2.81 range that Prof. Simcoe

³⁴⁹ Simcoe Report, ¶ 126.

³⁵⁰ Advertiser identifiers are anonymous in the data.

³⁵¹ In a first-price auction such as this, each bid incorporates the bidder’s valuation for the impression, reduced by a factor related to the bidder’s estimates of the distribution of rival bids (Krishna, Vijay, *Auction Theory*, Academic Press, 2010 (2nd Ed.), at pp. 13-16.). By focusing on the subset of auctions that an individual bidder wins and repeating Prof. Simcoe’s exercise, the resulting elasticities reflect both an individual advertiser’s demand elasticity and the competitive characteristics of the auctions that that advertiser wins.

³⁵² Exhibit 36, row [8]. According to Prof. Simcoe, he “prefer[s] to rely on a 6.18 percent price perturbation to measure the elasticity of both supply and demand. [He] prefers this price point because it is the optimal perturbation under the observed bunching of bids at floors...” Simcoe Report, Appendix H, ¶ 315.

³⁵³ Exhibit 36, row [6].